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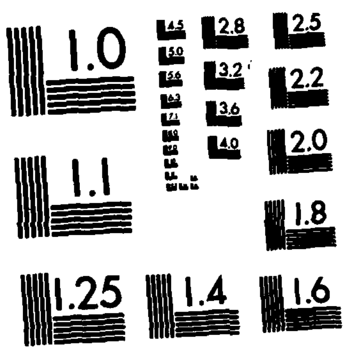

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FINAL REPORT: KNOWLEDGE AND SKILL DIFFERENCES IN NOVICES AND EXPERTS

Michelene T.H. Chi and Robert Glaser
Learning Research and Development Center
University of Pittsburgh

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Technical Report No. 7

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This final report describes the results from a research program whose ultimate goal is to construct a general theory of expert problem solving. In order to gain a broad data base, expert and novice performance was studied in two disparate domains, physics problem solving and navigating in a city. The various tasks which were used in each domain are described and their results are briefly summarized.

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Final Report: Knowledge and Skill Differences in Novices and Experts

For the period May 1, 1978 - July 31, 1981

Contract No.: N00014-78-C-0375

Michelene T. H. Chi and Robert Glaser

Contents

Overview

The objective of this research is to construct a theory of expertise based upon empirical description of expert problem solving abilities in complex knowledge domains. Our goal is to develop a theory that is representative enough to encompass both analytical types of problem solving (such as, solving problems in physics), as well as more spatial types of problem solving (such as maneuvering in a large-scale environment). Our work in the past three years has proceeded in these two directions. A major interest of the project is to determine the extent to which there are skills that are generalized across domains, and skills that are domain-specific. The practical outcome of our work is the identification of dimensions of expertise that can be taken into account in training and assessing the attainment of high-level competence.

Analytical Problem Solving

Background

Our research in problem solving in physics has been guided by the following three general questions. First, in what ways are experts more accurate and successful at solving problems than novices? Second, why do experts appear to spend more time in elaborate qualitative analysis of the problem (sometimes known as intuition and planning), before actually working with the appropriate equations? And third, on what bases do experts generate a different set of solution processes? In physics, experts appear to use a forward-working strategy, where they begin by generating equations involving the givens in the problem without much initial attention to the unknowns in the particular problem statement. A solution seems to be reached automatically as the initial equations involving the givens are systematically replaced by other equations involving the unknowns. In contrast, novices' solution processes appear more "backward" working, using more of the search strategies that have been identified in general problem solving theory; that is, the novice subject works from the goal (the unknown asked for in the problem) and sets up subgoals to reduce the difference between the goal and the givens (means-ends analysis).

These foregoing three questions stem from a primary task of the project, that is, the determination of the processes and structures that differentiate an expert from a novice. The three questions listed above derive from observations made in the literature of one or two subjects (Simon & Simon, 1978; McDermott & Larkin, 1978), and from our project work. (see Chi, Feltovich, & Glaser, 1981; Chi, Glaser, & Rees, 1982). Our basic notion at this point about what differentiates an expert from a novice is that the way in which the domain knowledge (physics) of the expert comes to be structured permits experts to spend more time "planning," to produce processes that are more forward-working, and to be more accurate and efficient. Hence, our empirical research has focused at locating the sources of expert-novice differences in problem solving by investigating how their knowledge is organized. We basically assume that there is no fundamental difference in the way experts and novices solve ordinary problems, but in physics, where their knowledge varies, processing outcomes interact with the knowledge the subjects have acquired.

In our preliminary proposal (February 1978), we attempted to find, from a review of past work, generalized features of expert problem-solving performance that occur in different knowledge domains. We concluded that the processes of importance can be categorized as consisting of the following components: encoding, search, planning, execution of solution, and checking. As planned, the focus of our first three years has been in the encoding stage of problem solving, and our interest centered on differences between the experts and novices in their encoding of physics problems. We reasoned that the encoding stage of problem solving was most important because it is at this point in time that a problem representation is constructed. Problem solving (such as the search for an exact sequence of equations) then proceeds, based upon the representation constructed.

This influence of encoding upon solution had been largely neglected in the problem solving literature in the past because problem solving in puzzle-like (knowledge-impoverished) domains with relatively confined knowledge bases require the selection of a set of limited operators. In such contexts, search (finding a solution) and planning (ways of finding a solution in the solution space) requires little complex construction of an initial representation. Hence, the involvement of encoding processes that appear to be especially significant in knowledge domains, has not been elaborated.

<u>Summary of Research Findings in Physics</u>

We have defined encoding grossly as the initial representation that the subject has constructed of a problem, before actually coming up with an exact solution. This point can be illustrated with some protocols of problem solving that we have collected (Chi, Glaser, & Rees, Study 1, 1982). Examining the protocols given by an expert and a novice on an inclined plane problem, we can segment the protocols into four major episodes. In both protocols, only one phase of the entire protocol (first episode for the expert's protocol and second episode for the novice's protocol) can be considered the qualitative analysis stage of problem solving, or problem encoding. It is during this stage of encoding that the essential inferences from the appropriate tacit knowledge are drawn. In this particular example, we postulated that the novice failed to solve the problem because he did not infer that the coefficient of friction is related to the angle. The novice <u>does</u> have the necessary equations to relate those two concepts, but does not have the explicit goal to do so, thus failing to solve the problem.

Since only one small episode of the entire problem solving protocol is involved with the generating of inferences and of relevant tacit knowledge, it is not surprising that in past work, other aspects of problem solving (equation generation) have received primary attention. Indeed, these aspects are the most prominent feature of the models of problem solving described by Simon and Simon (1978) and Larkin (1979) who have successfully modeled and simulated the sequence of equations that are generated in the process of solution. But results obtained in other work (cf. Hinsley, Hayes, & Simon, 1978) as well as our own protocol analyses have strongly confirmed the idea that most of the solution process is completed within the first minute or so as soon as the subject has "analyzed" the problem, even though the actual solution may take several minutes to generate. Consequently, our research goal in the past three years has been aimed at magnifying this initial stage of problem solving, by using a variety of methodologies, besides gathering protocols of problem solving.

Because problem representation must necessarily be constructed within the context of an existing knowledge structure, an objective of the project has been to focus on the difficult problem of depicting the representation of the knowledge base. Knowing how the knowledge base is represented will facilitate understanding of how a problem representation is constructed. Our work in the first three years has resulted in an initial specification of how declarative knowledge of mechanics is structured, and how this structure effects the problem representation. In the following sections, we briefly outline what we understand so far.

Encoding Problems into Appropriate Schemata. Using a sorting procedure, we have been able to confirm our hypothesis that problem solving begins with the initial identification of the appropriate schema to which it belongs. In our original proposal, we called this "priming" the right schema. We now have a variety of evidence to suggest that schemata of problem types do exist. First, when we ask subjects to sort problems, they can do so without any difficulty. Second, both experts and novices can sort problems rather quickly, taking about 30 to 45 seconds per problem, including reading time. This suggests that they are not basing their sort on the outcome of the solution processes, because solving these problems generally takes longer periods of time, in the order of several minutes. Third, we were able to uncover meaningful underlying structures of these categories through both a clustering type of analysis and direct questioning of the subjects. Both experts and novices were able to articulate the bases of their sorting to some degree. The bases of the experts' categories tend to be major principles of mechanics, such as the Conservation of Momentum principle, the Conservation of Energy principle, and Newton's force law. The bases of the novices' categories tend to be literal objects and concepts stated in the problem itself, such as inclined plane, a spring problem, and friction. (For more details, see Chi, Feltovich, & Glaser, 1981.) Furthermore, these schemata are hierarchical in nature, and we were able to validate the existence of a hierarchy through a procedure we call hierarchical sorting. This method requires the subjects to further sort the basic level categories that have already been sorted on the first attempt. This procedure revealed the layers of embedding that occur in the knowledge structure of the experts and novices. In particular, we found that the most naive novices had almost no embedding. That is, they were not able to differentiate their first level of sorting any further. As skill is acquired, the hierarchy develops into a complex tree with many levels of embedding. The most advanced experts, however, will often abandon the lowest level of sorting, and have actually fewer levels of embedding (see Chi, Glaser, & Rees, 1982, Study 4).

In general, our evidence so far indicates that using a schema-like framework to interpret our data is not unrealistic. However, it can facilitate further understanding of problem solving only if we can show: 1) that the organization and content of these schemata are basically different between the experts and novices, 2) that the same problem actually elicits different schemata for the experts and novices, even though the identical words in the problem statement were chosen as critical for solution, and 3) that it is this difference in the content of the schemata that causes difficulty in problem solving for the novices. We have some evidence to bear on parts 1 and 2, but no evidence yet to bear directly on part 3. In the following sections, we will first briefly discuss the two aspects for which we have some evidence for (parts 1 and 2) and then describe how we will attempt to gain information about the third aspect (the influence of schemata characteristic on solution processes) about which we have little information.

<u>How Schemata Are Elicited</u>. Using various procedures in different studies, we have arrived at two tentative findings regarding how the appropriate schemata are elicited. Our working hypothesis was that novices were not able to identify appropriate key words, i.e., important words that cue the appropriate schema. To answer this question, we asked subjects to judge how difficult a problem was after they read it, to circle the words or phrases that helped them make that decision, and to give reasons why they thought the problem was difficult. The general finding is that the same keywords are viewed as important by both novices and experts. However, experts generally consider fewer key words as important cues than the novices, and the key words that the

experts identify as important are subsets of those identified by the novices. There are very few instances in which experts identify certain key words that the novices do not (Study 8, Chi, Glaser, & Rees, 1982).

If experts and novices can pick out what the important key words are in a problem statement, what causes the novices difficulty in solving problems? There are two possible reasons. First, key words in the problem statement elicit derived (intermediate) knowledge for the experts, and not for the novices. For example, the fact that a problem involves a "pulley with friction" implies to the expert that "rotational kinetic energy" is involved. Such inferences are usually not made by novices. The evidence for this comes from the reasons provided by the experts for a problem's difficulty. Experts refer to this second-order intermediate knowledge, whereas the novices simply say in this case that a "pulley with friction" is involved. Hence, experts appear to store inference rules in their memory schemata so that the words "pulley with friction" directly elicit the additional knowledge that "rotational kinetic energy" in involved. Such knowledge links may be missing in novices.

A second reason for the effectiveness of experts and the difficulties of novices is that features in the problem statement can elicit a chain of inferences for the experts but not for the novices. We consequently postulate that the schemata that are activated for the experts are different from the novices. In the context of the example we have just cited, the expert would then base his choice of the appropriate schema on the knowledge "rotational kinetic energy," whereas the novice would base his selection on the knowledge that a "pulley with friction" is involved. This conjecture is supported by findings in another study (Study Four in Chi, Feltovich, & Glaser, 1981), where we explicitly asked subjects to state the reasons for how they would approach the solution of a problem. The reasons provided by the experts tended to be second-order derived knowledge that was not explicitly stated in the problem. Thus, referring back to the example, if a novice views the problem as one involving a "pulley with friction," then he will activate either his "pulley" schema or his "friction" schema, or some combination of both. In contrast, the expert, based on the knowledge that the problem is one about "rotational kinetic energy," will activate his "Conservation of Energy" schema, which has embedded in it both the "pulley" schema and the "friction" schema.

Based upon this evidence, we postulate that one reason that novices have difficulty solving problems is that they have activated only a lower level schema, whereas experts have activated a higher-level principle schema, which includes not only the lower-level schemata that the novices activate, but also additional knowledge about the relations between the embedded schemata and the high-level principle schema.

Contents of the Schemata. Errors in problem solving for the novice can arise not only from activating the "wrong" schema, but also from not having the appropriate content within a schema, had the "right" schema been activated. In order to examine the contents of schemata, we asked subjects to elaborate on schemata that we think they may have, such as an inclined plane. Their protocols can be analyzed in a number of ways. One way is to think of everything the subjects said as representing procedures so that we can convert their statements directly into production rules. This can be done by converting IF-THEN or IF-WHEN statements. With this technique of analysis, major difference between the experts' and novices' protocols becomes apparent. First of all, the experts' production rules contain explicit actions, such as F=MA, or Fs=0; whereas the novices' productions contain general actions, such as Find Mass or Find Coefficient of Static Friction. In addition, novices often possess a number of productions without explicit actions. For example, they have productions containing conditions such as "IF the block is at rest," but would not have actions attached to such a condition. This implies that novices know what relevant cues to look for in a problem, but did not know what to do with them. This is consistent with our additional finding that novices can pick out the important features in a problem statement. Finally, experts seem to know the conditions under which physics principles are elicited, suggesting that they have explicit links between their conditions and actions.

In summary, our data suggest that the contents of the schemata of experts and novices are different--the experts' schemata containing more procedural knowledge. We conjecture that this difference is a fundamental source of error for the novices. However, the problem is more complex. If we ask subjects simply to generate the equations that they might want to use in a problem involving an Inclined Plane, both novices and experts generate about the same set of equations. Hence, it is more than a simple matter of novices lacking procedural knowledge but what is also important is the linking of procedures with their appropriate conditions of applicability -- a consideration of major importance in training research and development.

Spatial Skill in Large-Scale Environments

Our theoretical conception of spatial skills in large-scale environments is that in many respects, spatial skills involve the same principles as other cognitive skills. One of the goals of our overall research project is to discover general principles of expertise across a variety of domains. In a report (Chase & Chi, 1980), we have described in some detail the relationship between cognitive skills and spatial skills. The most important principle of skill performance is that skill depends upon the knowledge base. In general, the more practice one has had in some domain, the better the performance, and from all indications, this increase in expertise is due to improvements in the knowledge base. In research on spatial skill, our effort has been directed toward an analysis of cab drivers' knowledge representation in large-scale environments.

Summary of Research Findings on the Representation of Large-Scale Environments

One of the current debates in cognitive psychology is whether spatial knowledge is represented as a visual image or as a set of propositions. We will remain theoretically neutral on this question, although we have outlined a more sophisticated theory based on hierarchical organization (Chase & Chi, 1980). Our research on expert-novice cab drivers suggests that large-scale environments are organized hierarchically. Local regions are interconnected by a network of global features. In the spatial layout of cities, this knowledge takes the form of a grid structure, or a network of relative spatial relations with respect to some prominent landmark. We have several findings to support this. First, without respect to skill, two-thirds of the cab drivers, when asked to draw a map of Pittsburgh, started their drawing with the river system, followed by placements of adjacent neighborhoods. We suggest that this is because the river system is a global feature which serves as a reference for placing the more local features (the neighborhoods). Second, cab drivers tend to recall neighborhoods together that lie in the same larger geographic area (such as the North Side); again, suggesting that neighborhoods are clustered into geographic regions. Third, when cab drivers are asked to place neighborhoods on a blank map of Pittsburgh, their locations tend to be distorted toward the point at downtown (where the three rivers come together). This again suggests that local neighborhoods are represented in memory in reference to some prominent landmark. Finally, when cab drivers were given pairs of well-known locations in the Pittsburgh area and asked to judge the direct distance between them, distances were greatly overestimated for locations separated by a neighborhood boundary. This result is another instance of a general phenomenon: Distance estimates across hierarchical boundaries are greatly overestimated (Stevens, 1976). In sum, we have provided a variety of evidence to support our notion that spatial knowledge is hierarchically organized (Chase, in press).

How is this spatial knowledge used? We suggest that there is a fundamental distinction between two kinds of processes: automatic procedures and inference rules. In his model of spatial cognition, Kuipers (1978) only makes use of inference rules, but a case can be made that people use automatic procedures as well. An automatic procedure is used when someone follows a well- learned route. At each choice point along a well-traveled route, a decision must be made as to which way to go, and this is normally accomplished smoothly, automatically and unconsciously. Nevertheless, people must make use of some information from the environment to follow a route. The usual suggestion is that people use visual "images" or "icons." That is, people have visual knowledge about each choice point stored in long-term memory, and as they approach these choice points, certain visual features serve to activate this knowledge; and associated with this knowledge are procedures that tell people what to do next. This is exactly the argument made in the cognitive skills literature as to why chess players and bridge players (Chase & Simon, 1973; Charness, 1979) can think of good moves, good evaluations, or whole sequences of moves or card plays rapidly and seemingly unconsciously. In each case, procedural knowledge is built into long-term memory and if the right visual information appears, this knowledge is activated and appropriate action is taken.

We have some evidence in support of the existence of automatic procedures. First, when cab drivers are asked to identify pictures of intersections, expert drivers can identify more intersections correctly when these occur in the secondary (or non-major) streets. This suggests that people do have visual knowledge about choice points stored in long-term memory, and they develop greater numbers of images of choice points with experience in driving in the city. Second, when cab drivers are asked to generate routes in the laboratory and later asked to take the same routes in the field, they all improved their routes by 25%. This, we conjecture, results from encountering intersections in the field, which matches the visual knowledge of their automatic procedures, and then triggering known routes associated with these cues.

The second kind of process that people use to operate on their spatial knowledge is the inference rule. These rules are used to derive knowledge that is not explicitly stored in memory. They may be used to fill in gaps in routes, to orient oneself in the environment, to perform geometric problem solving, and so on. Kuipers (1977, 1978) has provided a taxonomy of various types of inference rules for his model of spatial knowledge, and various examples of inferencing rules have been published (Chase & Chi, 1980; Stevens & Coupe, 1978). We have some data pertaining to the existence of inference rules. For example, when cab drivers are asked to point to the direction of a specific neighborhood, they tend to point in the direction of a nearby major street that leads to that neighborhood, suggesting that they are inferring the direction of the neighborhood from the direction of the street that reaches it.

So far, we have summarized results which suggest that spatial representation is hierarchically organized, irrespective of the skill level of the navigator, and that there appears to exist automatic procedures which both expert and novice navigators can use. What, then, differentiates the experts from the novices? Basically, experts have a richer knowledge base of streets, particularly the secondary ones. For example, the expert cab drivers can name more streets, particularly in the less familiar neighborhoods. Second, experts excel at generating routes between two locations. Experts' routes tend to be short whereas novices' routes tend to be long. Moreover, experts can often generate an improved route through the secondary streets.

Not suprisingly, expertise in taxi driving tended to emerge when drivers were asked to find routes, particularly routes through the lesser-known streets. The expert's ability to name and recognize more of these lesser-known streets than the novice is additional evidence that expertise involves a larger knowledge base acquired through years of practice.

The absence of any skill effects in the various cognitive mapping tasks lends little support to the idea that taxi drivers navigate by means of a map in the head. The results do, however, suggest that the large-scale representation of locations is hierarchically organized such that locations are nested within neighborhoods, neighborhoods are nested within large regions and larger regions are located with respect to more global features.

Finally, it is suggested that the hierarchical organization of neighborhoods is important in terms of economy of storage, and that this hierarchy serves as an integral part of planning a route. Hierarchical storage means that one need only store relative locations of places within a neighborhood. To retrieve the relative locations across a hierarchical boundary, one need only retrieve the relative location of the two neighborhoods and the relative location of each place with respect to its own neighborhood. to get from a location in one neighborhood to another location in a different neighborhood, it is suggested that the driver first find a route that connects the two neighborhoods, and then the rest of the route is either subsequently generated or it is filled in as the driver goes along. It is this "filling-in" process that involves automatic procedures. The driver can continue following a global plan until cues from the environment are encountered that trigger specific routes at choice points along a route. Some such process as this, it is suggested, underlies skill differences, as the number of these automatic procedures increases with experience.

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